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Utilizing structural equation modeling in the development of a standardized intervention assessment tool

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Abstract

There are numerous approaches to measuring multidimensional poverty; these include the Human Development Index and the Multidimensional Poverty Index among others [1]. However, a gap in the literature is found when intervention assessment tools are investigated. The idea of creating a standardized assessment tool would allow for a deeper understanding of poverty on a per community basis. Structural Equation Modeling (SEM) offers a robust platform in which to establish such a tool. An overview of SEM and several other general approaches to data aggregation are addressed. The notion of a standardized intervention assessment tool is discussed; this is focused on utilizing the SEM platform for this tool. Further, previous works by Divelbiss [2] and Voth-Gaeddert [3], [4] are discussed. To date SEM has shown to handle adaptability of differing environments positively. Divelbiss reported on the SEM multivariable poverty model within villages of Guatemala and Voth-Gaeddert reports on the applicability of this model used in a dissimilar environment in Brazil. These findings suggest feasibility in the utilization of a SEM platform for a standardized intervention assessment tool.

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1. Introduction

The Millennium Development Goals (MDGs) offer a broad spectrum of issues that are found in impoverished areas around the world. These goals include; eradication of extreme poverty, universal education, gender equality, reduction of child mortality, improved maternal health, combating prevalent diseases, promotion of environmental

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sustainability, and promoting global partnerships [5]. Many unaffiliated organizations are also working on these issues throughout the world. While some of these goals are on track, unfortunately the UN reports that, "accelerated progress and bolder action are needed in many areas" [5]. To address these issues more effectively a deeper understanding of how poverty is defined, is needed.

The term poverty is a broadly used word that encompasses a broad array of definitions. Independent researchers have slight deviations when defining and measuring poverty. This has led to varying methods of poverty measurement [6]. These measurements or indices recently have started incorporating a multidimensional approach. The term multidimensional poverty was first pioneered by Bourguignon and Chakravarty and Tsui and has manifested into a larger section of literature [7]. The concept of poverty being 'multi-dimensional' is highlighted by the spectrum of goals outlined in the UN's MDG's [5]. It is now broadly understood that poverty is multidimensional in character; the Human Development Index, for example, recognizes the role of health and education in addition to socio economic levels [8].

Currently there are many non-governmental organizations (NGOs) trying to effectively implement projects as well as government agencies that spend millions of dollars a year on poverty eradication. While a representative universal method for measuring poverty will be of great value, the immediate focus should be on effectiveness of foreign aid. The UN MDG report says that, "based on a *wide range of statistics*, the actions of all stakeholders are coalescing in the achievement of many of the MDGs. At the same time, a majority of items on the agenda remain incomplete [5]." On January 17th Engineers Without Boarders (EWB) national staff met to, "create a common understanding of the terminology [that they] will use to define EWB-USA's impact in the world and … theory of change [9]." "EWB-USA recognizes the need for a strong and coherent planning, monitoring and evaluation framework that promotes learning and improved performance [9]." Many dedicated organizations are looking for an effective way to measure their impact on the communities they are involved in. There is a clear need for a standardized assessment plan for post implementation of projects within foreign aid.

Previous work by Divelbiss, D., Voth-Gaeddert, L.E., and Oerther, D.B. [2] [3] [4] has incorporated the utilization of structural equation modeling (SEM) as an assessment tool. After a completed analysis in northern Guatemala [2] and preliminary studies in Brazil [3], [4], early indications are good for a community specific intervention assessment tool using SEM. A consistent result through all projects has been the lack of monetary income having the strongest direct effect to poor health within these particular communities. Significant work has been done by Schriner, A. and Oerther D.B. on a market based solution to offer an increase in monetary income globally [10]. Continued analysis of health correlations among education, economic status and sanitation will provide much needed direction for foreign aid efforts.

There is a strong body of work on how to measure multidimensional poverty globally. However, this differs from a project based assessment tool and it is felt that a gap in the literature is present within this particular subject. This paper will cover a brief outline of several *measures* of multidimensional poverty, including SEM. However, the larger focus will be on the use of the SEM platform for a universal community focused foreign aid assessment tool and examples from previous research.

2. Measuring Multidimensional Poverty

To analyze something as complex as poverty, multiple variables are often used in measurement. These particular measures often aggregate data to simplify or score the variables so they can be analyzed. Depending on the measured scores weights can be added to variables that report a higher or lower significance. Several types of poverty measures can be found in the literature, these include Composite Welfare Indicators; CWI [11], Multidimensional Poverty Index; MPI [1], Human Development Index; HDI [12], Water Poverty Index; WPI [13] Comprehensive Poverty Index; CPI, and Bourguignon-Fields Class of Poverty Indices; BFPI [14] among others. Each of these measures uses certain approaches to adjust for issues within the data. Some of these approaches include the Fuzzy Set Approach [15], Axiomatic approach [16], Information Theory Approach [17] [18], Distance Function Approach [19] and SEM Approach [20] among others. A number of articles offered reviews of multiple approaches, those papers include; Deutsch and Silber 2005 [21], Ningaye, P. et al. 2013 [11], Walker, R. et al. 2007 [22]. These approaches are complex and many refer to textbooks to grasp a full understanding of them. A brief overview is all that is offered in this text; a more in depth look is outside the scope of this paper, however, references to further literature can be found throughout each section.

The Fuzzy Set Approach has proven to be a powerful way of dealing with the vagueness of the term poverty. Fuzzy sets attempt to address two major issues within multidimensional poverty, 1) the identification of a poverty line or threshold and 2) the choice of a unit of analysis as well as of a measure, or better put; the aggregation problem [15]. It addresses the 'grey area,' that is poverty; when is a person no longer impoverished? Also, using fuzzy aggregation methods and weights, calibrations and single scores can be accumulated. For further analysis of the Fuzzy Set Approach see Lemmi, A. & Betti, G. 2006 [23].

The Oxford English Dictionary defines axiomatic or an axiom as, "a proposition that commends itself to general acceptance; a well-established or universally conceded principle." The axiomatic approach within multidimensional poverty is a list of rules that are followed within the literature when working in this particular subject area. For example, Tsui (2002) [24] provides a list of six axioms that unidimensional poverty measures are often assumed to satisfy: focus, symmetry, plication invariance, monotonicity, continuity and subgroup consistency [25]. This approach helps standardize analysis methods but can also lead to deviations within approaches.

Information Theory Approach is based around the concept of information expectancy. The expected result of an experience is established and a probability is then defined to have that result actually occur. The term entropy can then be introduced [26] [18], entropy is typically the expected information from the experience had. Miceli 1997 [27] was the first to apply this to multidimensional poverty. Miceli suggests that a measurement can be obtained from the distribution of the composite index. This index is an output from a function that describes the distribution of the probability of a result of an experience [21].

The Distance Function Approach is very useful in describing an outcome, such as standard of living, by a resource variable and a function variable of that resource. This is to help generalize other outcomes. In other words, using Sen's "capability approach" [28]; two vectors can be denoted; one being a resource vector (a person's resource) and the other being a functioning vector (how the individual uses the resource). To evaluate these two vectors a numerical representation is needed, this is typically in the form of an index [21]. A theorized distance function is then used to analyze the vectors. The issue that arises is a correlation between vectors and the composite error term. If this happens then the indicators could be biased. For more discussion on Distance Function Approach see Coelli et al. 2005 [19].

The SEM Approach is best served when analyzing a multidimensional or multivariate problem like poverty. It has been used extensively in the social science discipline but has recently become more widely used [29]. SEM enables the use of multiple regression equations simultaneously. By deriving composite indicators on the basis of the variance shared between the original (rather than by summing the variables), the attenuation of estimates caused by measurement error is avoided [22]. Confirmatory Factor Analysis (CFA), Exploratory Factor Analysis (EFA), Latent Growth Modeling (LGM), as well as other options, are available within the SEM framework. It can be used in both an exploratory or confirmatory analysis style. A further discussion of SEM can be found in the next section.

3. Structural Equation Modeling

Differences between the various approaches listed above are however much smaller as far as the determinants of multidimensional poverty are concerned [21]. This analysis may change with a new focus on using these techniques for a pre and post implementation assessment tool. To be able to effectively assess impacts of aid within a community, a large variety of factors need to be analyzed; direct and indirect effects need to be taken into account; and the assessment needs to be flexible with both time and error in measurement.

SEM allows for the incorporation and understanding of multiple relationships within a complicated reality. The use of latent variables is a concept within the area of SEM that allows the researcher to represent variables that can prove difficult to analyze through basic observations. Instead of using the idea of an index of indicators, SEM is able to avoid the errors accumulated from the summation of variables, whether weighted or not. The analysis of variance and covariance between multiple observable indicator variables allows for representation of these latent variables. For example, in a Brazilian household the latent variable, socio-economic status, can be represented in three indicator variables; building materials of the house, density of people within the house, and ownership of a personal boat. From these indicator variables a more robust representation can be obtained with the significant idea that less error will be found in the latent variable compared to other techniques. Basic statistical techniques can be used, such as maximum likelihood and others, to help estimate the path coefficients within the model.

The general SEM analysis is typically a two-step approach when working towards a confirmatory model. The definition of a 'model' can be vague, therefore a graphical representation of one type of SEM model is offered in Figure 1. In the figure, the latent variables are represented by circles and observable variables are represented by squares. This model is described as the full model. There are two parts to the full model, a measurement model and a structural model. The measurement model describes the relationships between the latent variables and the observable indicator variables. Using CFA (see [29]) the hypothesized model (covariance matrix) is compared to a data driven model (covariance matrix) using the Chi-Square test of model fit [30]. If the measurement model does fit the data via several tests of model fit indices [31], then the structural model can be assessed. Using the same style of model fit a model is either accepted or rejected. If the model is rejected adjustments can be made (with caution) and then retested. Once the model is accepted, direct and indirect effects can be assessed between latent and independent variables. This allows for the analysis of relationships between factors such as socio economic status, education, health, etc.

SEM can also be used in a purely exploratory style of analysis using EFA. If the researcher is uncertain as to which factor is described by which indicator, EFA allows for freedom amongst relationships within the measurement model. It is highly recommended within the literature that once a model is established through EFA, CFA is used with new data to test the model [29] [30].

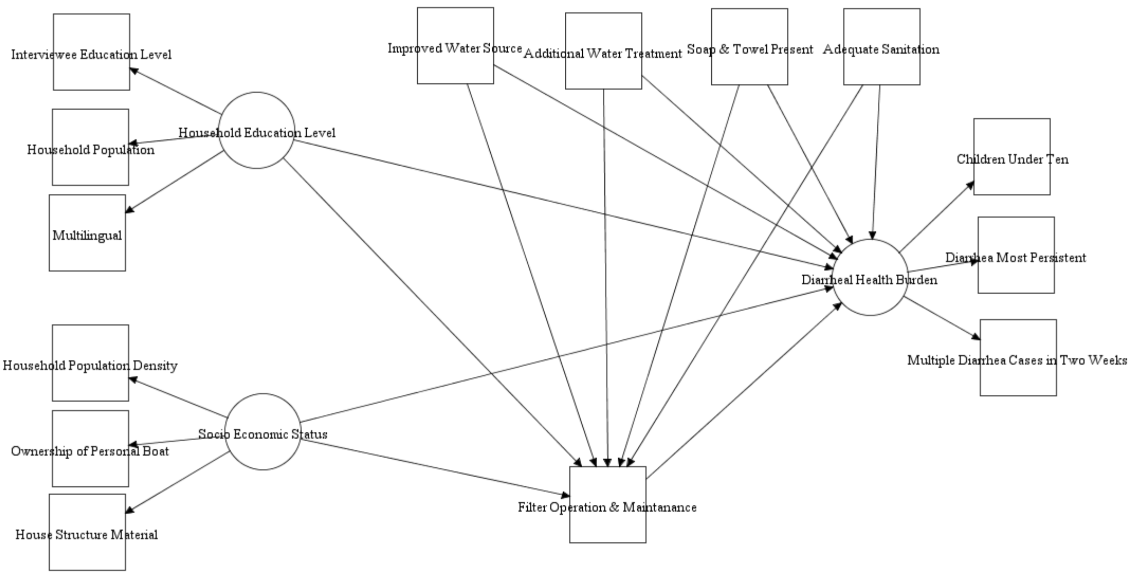

Fig. 1. Graphical display of a full SEM model with latent and observable variables

It is possible using SEM to create a composite index from a set of deprivation measures gathered in one year and to fix or 'freeze' it and apply it to later years, thereby allowing change in the composite deprivation index to be accurately measured over time [22]. This idea is the basis for creating an assessment tool on interventions within a particular community. A robust representation of factors in a particular community can be found through the general SEM analysis. Pre-implementation surveys allow for understanding of the multidimensional issues relevant to that community. Mid and post implementation surveys would allow organizations real time feedback on the impacts of the intervention. If the intervention is long term based a Latent Growth Model (LGM) analysis could potentially be utilized to predict future effects of the intervention.

LGM allows for further analysis by predicting what effect continued intervention would have on a community [29]. Walker 2007 says LGM can be thought of as taking a repeated measure of an indicator and creating two latent variables which summarize the level and the trajectory of the indicator in question over time for each case. A greater understanding of LGM is needed as it is a recent innovation within SEM, but shows much potential [32] [30].

Being able to correlate and analyze multiple types of variables through a robust graphical model introduces a tool that has potential to be used on many different levels of experimental analysis. For users that are not trained in SEM, such as development practitioners, the graphical models produced from the analysis can provide a user friendly interface. SEM has the potential to become a simple application tool required for all interventions within impoverished communities.

4. Current Work

SEM represents both a different way of analyzing data, and a different way of doing science [29]. Divelbiss et al. 2013 used this approach in Guatemala to begin to observe how SEM could be used within intervention assessments. "In rural health development practice, engineers and scientists must recognize the complex interactions that influence individuals' contact with disease-causing pathogens and understand how household habits may impact the adoption and long-term sustainability of new technology [2]." The term 'new technology' refers to the CAWST Biosand Filter which was the intervention that occurred within this area. With the utilization of SEM in a dual exploratory-confirmatory analysis methodology, Divelbiss successfully described the complex relationships that are associated with daily living. He reports that, "the results illustrate how demographics, infrastructure, and practices within the home have a significant effect on proper operation and maintenance of the Biosand filter." Specifically the Biosand filter was shown to help reduce health issues within the house. However, it was not among the top three most significant effects that reduced health issues. Therefore Divelbiss also reports, "Policy makers and development practitioners must recognize that single target interventions (e.g., improving water quality) have limited influence on the entire system." The reader is encouraged to study the full report (see [2]).

Although the results are location specific, the methodology behind the study allows for a greater understanding of the application of SEM. Divelbiss also was able to highlight a potential model within multidimensional poverty. To investigate the applicability of this model to other regions a second study site was selected. In March of 2013 a complimentary feasibility study was directed by Voth-Gaeddert et al. 2013 [3] in several rural villages located west of Santarem, Para, Brazil along the Amazon River. Once the feasibility study was found to be successful a pilot study was then run [4]. The larger case study is ongoing but preliminary reports suggest the structural model developed by Divelbiss in Guatemala is suitable for a dissimilar region such as the Amazon. The underlying issue that affects all measurement tools for multidimensional poverty is the selection of indicator variables. However, SEM offers several different options to help decipher implications of different indicators.

A second finding among all three studies [2] [3] [4] was of the significance of sufficient monetary income. The factor, socio economic status, had higher direct and indirect effects on health then the intervention itself. While the intervention itself remains important, the data suggests a larger focus on monetary income and job creation. The idea of using the needs of an information-based economy to provide work through a market based strategy is being investigated by Schriner and Oerther. They are offering a platform (Pula Cloud) in which human computation work can be done benefiting both the worker (market driven to developing countries) and the requester (needs primarily from wealthier areas). Further study is encouraged to the reader in this subject (see [10]).

5. Conclusion

Continued efforts for solutions to poverty [10] and the evaluation of these solutions [3] [4] are needed. While large scale, government driven approaches are taking place, a partnered accountability towards these efforts will ensure appropriate interventions. A grass roots community based assessment tool can offer accountability on a large scale if implemented correctly. SEM has the potential to be used as a platform for this tool. The literature shows an increase in the interest and application of SEM throughout multiple disciplines [29]. While a holistic positive trend of diminishing poverty is taking place, billions are still suffering [5]. While effective, a danger of taking a holistic approach to solving poverty is the consequence of particular groups of people being left behind. Global accountability through assessments is needed to ensure a standard of living that every person deserves.

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